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LCA FOR AGRICULTURE

MEXALCA: a modular method for the extrapolation of crop LCA

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Abstract
Purpose Life cycle assessment (LCA) is widely used for the environmental assessment of food products, but difficulties arise when evaluating large portfolios of food products or when faced with a diversity of sources of ingredients and/or frequent changes of suppliers. In such situations, a specific, in-depth assessment of each ingredient is not feasible, and screening approaches using a few LCIA (Life Cycle Impact Assessment) results are not recommended. The goal of this paper is to propose an intermediate solution between a screening assessment using limited data and specific LCA for all products considering all sources of ingredients.
Methods The extrapolation method presented here [Modular EXtrapolation of Agricultural LCA (MEXALCA)] allows deriving LCIA results for a crop in a specific (target) country using the LCIA data of the same crop in another (original) country. The existing crop inventory (LCI) is split into nine modules corresponding to the main on-field and post-harvest activities, each associated to its key farming input. This approach reduces the complexity of the inventories, and data collection is focused on nine inputs in the target country. Additionally, data can be approximated by means of statistical estimators if necessary. Impacts per unit of farming input are calculated for each module in the original country and combined with the quantity of farming inputs in the target countries in order to determine the impacts in the latter.
Results and discussion Combining MEXALCA with available national statistics provides the means for a rapid evaluation of environmental impacts of a given crop for all producing countries globally and the determination of their statistical distribution. The range of the impacts for a number of crops was determined, and a sensitivity analysis with values derived from national statistics was conducted. Validation of the method showed a good performance for the evaluation of energy demand, ozone formation, and global warming potential. The method was inaccurate for eutrophication and acidification and not suitable for toxicity impact categories.
Conclusions and recommendations Extrapolation of agricultural LCIAs using statistical data and existing inventories is feasible. Compared with many streamlined LCA approaches, it does not discard processes nor jeopardise the understanding of the production system. MEXALCA shows benefits in terms of the amount of data and time required and allows for data generation on a multi-country scale. It appears promising for an assessment of products from various origins and may also be useful for the extrapolation of one product to another. The method is suitable for environmental assessments at the regional or global scale and to fill data gaps in traditional LCAs. However, extrapolation should not replace a conventional LCA for the assessment of a specific product, and particular caution should be exercised for spatially dependent impact categories such as eutrophication or acidification.

Keywords Agricultural production · Crop production · Bio-based products · Data variability · Geographical extrapolation · Life Cycle Assessment (LCA) · Life Cycle Inventory (LCI)

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1 Introduction

During the past years, environmental awareness of consumers and authorities has considerably increased. For some, environmental considerations have become an additional criterion to price, quality, design or ethics when purchasing a product or service. In response to this growing concern, numerous ‘eco-labels’ have been stamped on consumer goods, and many ‘greenhouse gas calculators’ are now available for consumers and companies. Life cycle assessment (LCA) is preferred for the environmental assessment of products since it takes into account all environmental burdens caused by a production system. Currently, several initiatives which aim at standardising carbon footprint approaches—e.g. BSI (2008); ISO (under development); activities of WBCSD/WRI—towards more robust methods are heavily informed by LCA methodology.

Many companies are interested in assessing the environmental impacts of their product portfolios rather than one or two of their individual products, in order to support strategic decision making (e.g. setting and tracking emissions targets; guiding innovation investments, etc.). For such companies, data availability is a central issue, and the choice of a methodology for environmental assessment is often related to this aspect. They need sound and representative assessment results providing reasonable estimates of the orders of magnitude and variability associated with different management options at the regional and global scales. However, whilst most ‘greenhouse gas calculators’ currently have a basic design and are fed with fairly limited databases, LCA and sophisticated carbon footprint methods require a lot of data, which are not readily available. The results obtained with most ‘greenhouse gas calculators’ are too restricted for strategic management, since these tools do not depict the differences in environmental impacts of the various production chains. Assessment of each commodity provided by each supplier using a complicated method like LCA can be impracticable due to the challenging search for data. In the context of Fast-Moving Consumer Goods, where suppliers and supplying regions may vary, or for complex products containing many ingredients, a detailed LCA study approach is not possible at a product portfolio level.

Different strategies to overcome the lack of relevant LCI and LCIA data are currently in use:

- Use of *proxy data* and *generalisation*: Use of inventories or even impact assessment results (e.g. use of carbon footprint figures for ‘similar’ products) developed for a situation different to the one studied is a wide-spread practice (Milà i Canals et al. 2010). Temptation may be high to use the LCI or LCIA data available in LCA software without any adaptation to the studied situation (location, technology and product). In some cases, specific values for one single product are generalised to represent a whole product category (e.g. one LCIA value for Swedish cheese to represent all dairy products). This can be questionable since representative data for the studied situation are required for LCA in order to draw solid conclusions (Ciroth and Srocka 2008; Ross and Evans 2002; Steinberger et al. 2009)
- *Streamlined LCA*: They usually rely on simplified LCI and emission models which require less data and depend on several hypotheses (Kuan et al. 2007; Zah et al. 2009). Common streamlining strategies may involve the removal of some processes or, for example, using constants and coefficients instead of a physical representation of a process (Koffler et al. 2008; Meisterling et al. 2009; Todd and Curran 1999). These approaches can potentially lead to involuntary omissions of important aspects (Weitz and Sharma 1998) and entail large errors in the results.
- *Adaptation of inventories/extrapolation*: Data available in the databases can be adapted properly for the study. These adaptations can concern an isolated part of the inventory (Lewandowska et al. 2008) or consist in a systematic procedure as done by extrapolation. Some extrapolation approaches have been suggested e.g. for transferability of LCI data between countries (Makishi Colodel 2008).

A solution combining the highly informative value of LCA with a reasonable systematic generalisation is thought to be appropriate for the assessment of large portfolios where ingredients are sourced from a variety of regions/suppliers or they represent a low percentage of a complex product.

This paper presents a new extrapolation method for deriving crop LCIA data. It is intended to save time compared with a classical detailed and specific agricultural LCA and to facilitate the creation of generic datasets (e.g. for production on the global scale) while establishing the level of variability. The goal is to offer more robust results than with streamlined LCAs, and data that are more representative than the use of proxy data. We first describe the concept of extrapolation and the proposed method (Section 2). We demonstrate the applicability of the method for wheat and show some results for this crop in Section 3. A sensitivity analysis follows in Section 4, and the method is validated in Section 5. We discuss the method (Section 6) and conclusions are drawn in Section 7.

2 Extrapolation method

We propose an extrapolation method for LCIA data of crop production, the MEXALCA method (Modular EXtrapola-

tion of Agricultural LCA). Characteristics of the method include:

- Independent of the choices made for system modelling, emission models or LCA software.
- Restricted to the assessment of the crop production phase only.
- Restricted to the assessment of commercial production in a conventional way (organic production and subsistence agriculture were not evaluated).
- Boundaries set at the farm gate.
- Calculations first performed per cultivated area and then converted per kilogramme of raw product using the yield.

MEXALCA enables:

- A rapid assessment of environmental impacts attributable to the agricultural production system in all producing countries.
- The determination of the statistical distribution of the impacts at different scales—global or multi-country scales.

This innovative method provides an assessment of the variability of the impacts associated with an agricultural production system, i.e. the range of the likely values for the impacts.

The functional unit '1 kg of product at the farm gate' is used to express the results in this paper.

Industrial processing of the product and transport are not considered. The focus on the impacts caused by the production is explained by the fact that they usually dominate the whole life cycle of bio-based products (Foster et al. 2006; Guignard et al. 2009). Furthermore, industrial processing or transport are usually much more standardised and can thus be estimated quite easily. These aspects as well as more specialist farming practices, such as organic farming, could be included in MEXALCA if desired, but would require some adaptations of the method.

2.1 Conceptual background

Extrapolation refers to the creation of new data points outside a set of known data points. In the LCA context, it means that new LCIA data are created using existing LCIA data by adapting them to the situation of interest. Several extrapolation types can be distinguished in LCA:

- Product extrapolation: LCIA data for a product are adapted to another product (e.g. rye from wheat),
- Technology extrapolation: LCIA data for a production technology are adapted to another technology (e.g. organic from conventional),
- Geographical extrapolation: LCIA data for a production in a given location are adapted to the production in another place (e.g. Canada from US).

Our initial research has focused on geographical extrapolation, although the same method could be explored for the other two types in future studies.

Multivariate statistical methods have shown that impact category indicators can be grouped into a few classes (Mouron et al. 2006; Nemecek et al. 2005). Mouron et al. (2006) found that these classes show a close relationship with key farming inputs. This led to the concept of a modular crop LCA, where the different modules can be varied independently from each other to a certain extent.

MEXALCA relies on a linear relationship between the environmental impacts and a limited set of key farming inputs. This relationship is firstly determined for a situation where inputs and impacts (LCI and LCIA) are known and then used to obtain the impacts (LCIA) in case of new values for the inputs (LCI). The set of key farming inputs should be small enough and solely contain variables for which values are accessible, in order to make the approach practicable. But, this set should also be large enough and the variables adequately chosen, in order to reflect the complexity of the system and to get relevant results.

The current set of impact categories considered in the method are those proposed by Nemecek et al. (2010) and also water use (total abstracted water for irrigation), which is relevant for the current debates about sustainability of agro-products. Land use and water use are handled in a simple manner in this study by summing the land area and volumes of water used and have an illustrative value. The selection of impact categories and assessment methods used in this study is presented in Table 1.

Our method is flexible and could easily be adapted for additional impact categories if required for particular purposes.

2.2 Modular extrapolation of agricultural LCA

The MEXALCA method is based on the procedure outlined in the following sections, where the term 'original' refers to the country or countries where LCI and LCIA data are already available and 'target' to the one for which LCIA data have to be extrapolated. For example, if LCI and LCIA data are available for wheat production in the US and the environmental impacts of wheat production in Canada are assessed using MEXALCA, the US is the original country and Canada is the target country.

Table 1 Mid-point impact categories and impact assessment methods used in MEXALCA

Impact category	Method	Unit
Demand for non-renewable energy resources	Frischknecht et al. (2004)	[MJ-eq (kg product)$^{-1}$]
Global warming potential over 100 years (GWP)	IPCC (2006)	[kg CO_2-eq (kg product)$^{-1}$]
Ozone formation potential	EDIP97: Hauschild & Wenzel (1998)	[kg ethylene-eq (kg product)$^{-1}$]
Eutrophication potential	EDIP97: Hauschild & Wenzel (1998)	[kgN-eq (kg product)$^{-1}$]
Acidification potential	EDIP97: Hauschild & Wenzel (1998)	[kg SO_2-eq (kg product)$^{-1}$]
Terrestrial ecotoxicity potential	CML01: Guinée et al. (2001)	[kg 1,4-DCB-eq (kg product)$^{-1}$]
Aquatic ecotoxicity potential	CML01: Guinée et al. (2001)	[kg 1,4-DCB-eq (kg product)$^{-1}$]
Human toxicity potential	CML01: Guinée et al. (2001)	[kg 1,4-DCB-eq (kg product)$^{-1}$]
Water use	Total amount of water abstracted from water bodies ("blue water" according to Milà i Canals et al. (2009))	[m^3 (kg product)$^{-1}$]
Land use	Total land occupationCML01 : Guinée et al. (2001)	[m^2year (kg product)$^{-1}$]

2.2.1 Original inventory construction

At least one inventory for the original country is needed. This is typically a detailed inventory for the crop cultivation in the given country or a mean inventory obtained by averaging several inventories. The second option is preferable and makes the extrapolation more robust, but requires a greater time investment. Inventories corresponding to special agricultural situations (e.g. country with extreme rainfall) should be avoided as original inventory.

At this step, the functional unit is 'one cultivated hectare during one growing season (GS)' for annual crops and 'one cultivated hectare during 1 year' for permanent crops. We will further use 'one cultivated hectare during one GS' in this paper in order to keep the units readable, thus assuming that we consider an annual crop.

2.2.2 Inventory split

This step aims at reducing the set of key farming inputs to be explicitly considered for the impact assessment. The original inventory contains dozens or hundreds of data (material and energy flows), and an extrapolation of each would be extremely laborious. These data have to be grouped meaningfully in a few subsystems. The grouping subsystems in MEXALCA correspond to the main operations known to dominate the environmental profile of agricultural systems (Brentrup et al. 2004; Hospido et al. 2009; Milà i Canals 2003; Milà i Canals et al. 2006; Nemecek et al. 2005) and are named 'modules'. They are listed in the first column of Table 2. The grouping of the inventory data has to be done manually: the user has to assign each flow to a different module. It can be seen as an aggregation at the level of the individual data (flows): they are grouped into some subsystems (modules). At the level of the whole inventory, it is a split: the whole system is split in nine modules. The split is done according to two criteria: input group and type of emission. The input group is used to determine all impacts related to the production of the input (like N fertilisers) and its application in the field (e.g. topdressing with nitrogen). The direct field emissions have to be assigned to the corresponding module. N emissions are assigned to the module 'N fertiliser use', P emissions to 'P fertiliser use' and heavy metal emissions to the 'basic cropping operations'. This procedure does not discard any data of the original inventory. It results in no change in the mass and energy flows of the system described. To check consistency, the user may calculate the impacts using the original inventory and the split inventory (Section 2.2.3) and will find identical results.

One key physical farming input is associated with each module when possible (third column in Table 2). It is the case of the modules 'N fertiliser use', 'P fertiliser use', 'K fertiliser use', 'Pesticide use', 'Irrigation' and 'Drying'. For the modules related to machinery use, an intensity index for the level of mechanisation is associated with the module instead of a physical input.

2.2.3 Calculation of the impacts per unit of farming input in the original country

Since MEXALCA relies on a linear relationship between the environmental impacts and some key farming inputs, the impacts per unit of farming input have to be evaluated. The linear relationship can be formalised mathematically (Eq 1).

$$EI_i = \alpha_i + \beta_i M + \gamma_i T + \delta_i N + \varepsilon_i P + \varsigma_i K + \eta_i A + \theta_i W + \kappa_i D \quad (1)$$

EI_i is the environmental impact i. Here, i is equal to 1 to 10, since we consider ten impact categories (see Table 1).

Table 2 Modules in MEXALCA

Modules	Description	Key farming input	Unit of the associated input variable
Basic cropping operations	All the inventory inputs and flows related to the conceivable minimal management of a crop: sowing and seed input, machinery operations for base fertilisation and harvest. This is considered to be independent of the specific situation.	No input required. This part of the inventory is assumed to be the same in the original and in the target country; it is not extrapolated.	–
Variable machinery use	All possible uses of machinery which are not absolutely necessary to cultivate a crop but which are employed in many cases for a higher yield or to reduce field labour (mechanical weeding for instance).	Index for mechanisation intensity (M).	–
Tillage machinery use	The machine inputs used for ploughing operations.	Index for tillage intensity (T)	–
N fertiliser use	The amount and type of nitrogen-based mineral fertilisers, machinery use for topdressing application and direct field N emissions.	N fertilisers input (N)	[kgN applied $(ha)^{-1}(GS)^{-1}$]
P fertiliser use	The amount and type of phosphorus-based mineral fertilisers plus the direct field P emissions.	P_2O_5 fertilisers input (P)	[kg P_2O_5 applied $(ha)^{-1}(GS)^{-1}$]
K fertiliser use	The amount and type of potassium-based fertilisers.	K_2O fertilisers input (K)	[kg K_2O applied $(ha)^{-1}(GS)^{-1}$]
Pesticide use	All the inputs and flows related to the pesticides applied to the crop.	Pesticides input (A)	[kg active ingredient applied $(ha)^{-1}(GS)^{-1}$]
Irrigation	The amount of water for irrigation including energy for pumping and infrastructure.	Water for irrigation (W)	[m^3 irrigation water $(ha)^{-1}(GS)^{-1}$]
Drying	Drying of the product using fossil energy, including infrastructure.	Water to be evaporated (D)	[kg water evaporated $(ha)^{-1}(GS)^{-1}$]

M, T, N, P, K, A, W and *D* are the key farming inputs as shown in the third column of Table 2.

α_i, β_i, γ_i, δ_i, ε_i, ζ_i, η_i, θ_i and κ_i are the impacts per unit of farming input for the environmental impact *i*. α_i corresponds to the unavoidable impacts for growing a given crop. They are assumed to be constant across the world. They are obtained by making a LCIA on the subsystem ‘basic cropping operations’. β_i corresponds to the impacts caused by the variable use of machines in the original country. They are obtained by making an LCIA on the subsystem ‘variable machinery use’. γ_i corresponds to the impacts caused by the use of tillage machines in the original country. They are obtained by making a LCIA on the subsystem ‘tillage machinery use’. δ_i ε_i ζ_i correspond to the impacts caused by 1 kg N; 1 kg P_2O_5 and 1 kg K_2O applied on 1 ha during one GS, respectively. They are obtained by making a LCIA on the normalised subsystems ‘N fertiliser use’; ‘P fertiliser use’ and ‘K fertiliser use’. The normalisation is done by dividing the entire inventory data of this subsystem by the number of kg N; kg P_2O_5 and kg K_2O applied on 1 ha during one GS in the original country, respectively. η_i corresponds to the impacts caused by 1 kg active ingredient applied on 1 ha during one GS. They are obtained by making a LCIA on the normalised subsystem ‘pesticide use’, normalisation done by dividing all inventory data of this subsystem by the number of kilogramme active ingredient applied on 1 ha during one GS in the original country. θ_i corresponds to the impacts caused by an irrigation of 1 m^3 applied on 1 ha during one GS. They are obtained by making a LCIA on the normalised subsystem ‘irrigation’, normalisation done by dividing all the inventory data of this subsystem by the amount of irrigation water applied (cubic metre per hectare) during one GS. κ_i corresponds to the impacts caused by the evaporation of 1 kg of water in crop grown on 1 ha during one GS. They are obtained by making an LCIA on the normalised subsystem ‘drying’, normalisation done by dividing all inventory data of this subsystem by the number of kilogramme water evaporated per hectare during one GS.

The LCIA for each module can be carried out using any LCA software; we used TEAM™ (www.ecobilan.com/uk_team.php).

2.2.4 Determination of the amount of farming inputs in the target country

The amount of key farming inputs (*M, T, N, P, K, A, W, D*) has to be determined in the target country.

M and *T* do not correspond to physical farming inputs but to intensity indices. *M* depicts the relative mechanisation intensity in the target country as compared with the original country. It is used to adjust the impacts related to the variable machinery use in the original country (β). *T* expresses the importance of tillage in the target country. It is used to adjust the impacts related to the tillage machinery use in the original country (γ).

N, P, K, A, W and *D* are physical farming inputs. They are used to convert the impacts per unit of farming input (δ, ε, ζ, η, θ and κ, respectively) into the total impacts in the target country.

Sometimes data are available for the farming inputs (*M, T, N, P, K, A, W, D*) in the target country, typically in countries having national statistic services. In those cases, such data should be directly used, and the reconstitution of the impacts in the target situation is straightforward (Section 2.2.5).

However, data on the farming inputs can be difficult to obtain. In this case, estimators can be used to approximate the missing farming inputs. We developed estimators based on agricultural indices for *M, T, N, P, K, A, W* and *D*. Their calculations as well as the values of agricultural indices are presented in the electronic appendix.

Agricultural indices indicate the intensity of use of each farming input and also indirectly reflect the yield level. Data used for the agricultural indices originate from FAOSTAT (FAO 2009). For instance, the intensity of nitrogen fertilisation is given by the average amount of N fertilisers applied per hectare in the whole country, normalised by the corresponding world weighted average. These indices are country-specific but not crop-specific.

The estimators are based on the ratio of the yields in both the target and the original country, on the ratio of the agricultural indices in both countries and on the amount of faming input in the original country. As an example, the estimator of the amount of N fertiliser used in the target country is given in Eq 2.

$$\widehat{N}_t^c = N_o^c \frac{Y_t^c}{Y_o^c} \sqrt{\frac{\mathrm{ind}_t^N}{\mathrm{ind}_o^N}} \tag{2}$$

$\widehat{N}_t^c$ is the estimator for the amount of N fertiliser used in the target country [kgN (ha)$^{-1}$(GS)$^{-1}$], $N_o{}^c$ is the amount of N fertiliser used in the original country [kgN (ha)$^{-1}$(GS)$^{-1}$], $Y_t{}^c$ is the yield in the target country [kg raw product (ha)$^{-1}$(GS)$^{-1}$], $Y_o{}^c$ is the yield in the original country [kg raw product (ha)$^{-1}$(GS)$^{-1}$], $\mathrm{ind}_t{}^N$ is the intensity of nitrogen fertilisation in the target country [−] and $\mathrm{ind}_o{}^N$ is the intensity of nitrogen fertilisation in the original country [−].

For the farming inputs which influence the yield directly (fertiliser inputs, variable machinery use, pesticide use), the yield is introduced explicitly in the equations. As the yield is already indirectly included in the agricultural indices, this would result in a double counting. To avoid this, we take the square root of the ratio of the agricultural indices. This means that both factors, namely the yield and the farming context are of about the same magnitude.

2.2.5 Reconstruction of the impacts in the target country and conversion

The impacts are determined in the target country by resolving Eq 1. The impacts are obtained per cultivated hectare and GS. They are further divided by the yield (from FAO 2009) in order to get the impacts per kilogramme of product. The same procedure is applied on the inputs.

2.2.6 Determination of median impacts and quantification of the variability

Using the estimators (Section 2.2.4), the impacts can be evaluated for all producing countries. The statistical distribution (median and several quantiles) of the impacts and of the inputs is defined in MEXALCA at the global or at the multi-country scales. It takes the different production volumes of the countries into consideration. For example, the median (50th percentile) impact of the cumulated production means that 50% of the production is estimated to have an impact below this value and 50% above this value.

3 Method application

The MEXALCA method is currently implemented as a set of almost fully automated Excel spreadsheets. Manual operations are needed for the modularisation of the original inventory (Section 2.2.2) and for the computation of the impacts per unit of farming input (Section 2.2.3). The other operations in MEXALCA (Sections 2.2.4 to 2.2.6) are automated. So far, MEXALCA (with the use of the estimators) has been applied to eight crops (wheat, rye, barley, potato, carrot, protein pea, black pepper and cocoa). It has demonstrated a good practicability as well as important time saving benefits as compared with a traditional LCA approach. The impacts in all producing countries were determined in a few hours for each crop. The statistical distributions of the inputs and of the impacts worldwide were calculated at the same time.

We present the statistical distribution of the impacts for wheat based on 123 producing countries (corresponding to the wheat-producing countries according to FAO (2009)) as an example. The ecoinvent inventory ‘wheat grains IP at farm, CH’ for Switzerland (Nemecek and Kägi 2007) is used (i.e. Switzerland is the original country) and adapted to the purpose of our study: straw is removed since straw was assumed not to be a co-product in most countries; organic fertilisers are not considered since our method solely deals with mineral fertilisers so far; irrigation is adapted in order to avoid the extrapolation of a null value (Section 2.2.1). This adapted inventory is then modularised (Section 2.2.2). The impacts per unit of farming input are calculated for each module (Section 2.2.3). The impacts for each country producing wheat were determined using the impacts per unit of farming input and the estimators for the farming inputs in all producing countries (Sections 2.2.3 to 2.2.5). The statistical distribution of the impacts of wheat production across the world is then determined (Section 2.2.6). The median and various quantiles of the impact distribution per kilogramme of wheat are shown in Table 3. For example, 10% of the wheat grains worldwide are produced with less than 4 MJ-eq per kg.

4 Sensitivity analysis

Determining the statistical distribution of the inputs used worldwide for the production of a crop allows the practitioner to perform a sensitivity analysis based on realistic variations. Such a sensitivity analysis is more relevant than a sensitivity analysis where the inputs are arbitrarily varied (±50% for instance), since it reflects a good approximation of the actual variability ranges in the crop management.

The sensitivity analysis was performed by varying each farming input (i.e. each module input) consecutively, first setting one of them to its tenth percentile-value and then to its 90th percentile-value. The mean absolute deviation around the median is finally calculated (Eq 3).

$$S_{EI_i,j} = \frac{1}{2}\left(\left|\frac{(EI_i)_{j\_q10\%} - (EI_i)_{j\_q50\%}}{(EI_i)_{j\_q50\%}}\right| + \left|\frac{(EI_i)_{j\_q90\%} - (EI_i)_{j\_q50\%}}{(EI_i)_{j\_q50\%}}\right|\right) \tag{3}$$

$S_{EIi,j}$ is the sensitivity of the environmental impact i to the farming input j. $(EI_i)_{j\_q10\%}$ is the environmental impact i obtained with the farming input j set at the value corresponding to its 10% quantile (all other farming inputs are set to their median value). $(EI_i)_{j\_q50\%}$ is the environmental impact i obtained with all farming inputs set at their median value. $(EI_i)_{j\_q90\%}$ is the environmental impact i obtained with the farming input j set at the value corresponding to its 90% quantile (all other farming inputs are set to their median value).

The same procedure is followed for each farming input j (i.e. for each module) successively for each environmental impact i.

The results of the sensitivity analysis for wheat are presented in Table 4.

These results are important in terms of data collection strategy. They enable us to identify the most relevant inputs, for which an effort should be made to acquire good quality data. The inputs identified as less relevant could be replaced by proxies, depending on the goal of the performed study. Furthermore, the most important improvement potentials can be recognised.

The results show that N fertiliser use is a key driver for many impacts. Irrigation is, of course, determining the water use, but is also highly relevant for energy, GWP and ozone formation potential. Pesticide use dominates the toxicity

Table 3 Statistical distribution of the impacts per kilogramme of wheat based on 123 countries

Impacts per kiloggramme of wheat grains	Quantiles (% of cumulated world production)				
	10%	25%	50% (median)	75%	90%
Non-renewable energy [MJ-eq]	3.9E 00	4.4E 00	5.8E 00	8.8E 00	1.1E 01
GWP 100a [kg CO2-eq]	3.5E-01	4.7E-01	5.5E-01	6.4E-01	7.0E-01
Photochemical ozone formation [kg C2H4-eq]	1.1E-04	1.5E-04	1.7E-04	2.2E-04	2.7E-04
Nutrient enrichment [kgN-eq]	8.6E-03	1.6E-02	2.3E-02	3.1E-02	3.7E-02
Acidification [kg SO2-eq]	4.3E-03	5.8E-03	8.1E-03	1.0E-02	1.2E-02
Aquatic ecotoxicity 100a [kg 1,4-DCB-eq]	5.1E-02	5.8E-02	1.0E-01	1.3E-01	1.9E-01
Terrestrial ecotoxicity 100a [kg 1,4-DCB-eq]	1.3E-03	1.7E-03	2.5E-03	3.2E-03	4.7E-03
Human toxicity 100a [kg 1,4-DCB-eq]	9.0E-02	1.1E-01	1.4E-01	1.8E-01	2.2E-01
Water use [m^3]	1.3E-02	4.1E-02	1.7E-01	4.7E-01	6.6E-01
Land use [m^2year]	1.6E 00	2.4E 00	3.8E 00	4.4E 00	5.5E 00

The median as well as several quantiles are shown for key impacts of wheat production on the global scale

categories. Machinery use is of medium importance only, while P and K fertilisers and drying are less important for the impacts of wheat crop. This study confirms nitrogen-based fertiliser input as a key driver for GWP, nutrient enrichment and acidification (Milà i Canals et al. 2006), pesticide input is important for ecotoxicity impact category (Antón et al. 2004) and irrigation is a dominant input in many crops.

Fig. 1 Comparison between results of the MEXALCA method and ecoinvent datasets per kilogramme product using all crops which have been assessed with MEXALCA and which are also included in ecoinvent V2.01. The method was tested for these crops with all countries available in ecoinvent: barley in France, Germany, Spain and Switzerland; wheat in France, Germany, Spain, Switzerland and USA; rye in the European Union and Switzerland; potatoes in Switzerland and USA; protein pea in France, Germany, Spain and Switzerland. Energy demand is depicted in (**a**), GWP in (**b**), ozone formation in (**c**), nutrient enrichment in (**d**) and acidification in (**e**)

5 Validation of the method

A first validation of MEXALCA has been performed using LCIA results available in ecoinvent V2.01 (ecoinvent Centre 2007). The goal is to assess the quality of the extrapolation, i.e. its ability to produce new LCIA results which are consistent with the original LCIA results. Since we used original inventories which are close to the ecoinvent inventories (similar system description, emission models and impact assessment methods), MEXALCA should deliver LCIA results which are close to the ecoinvent LCIA results, if it performs well. The MEXALCA results are shown against the ecoinvent LCIA results of selected crops in Fig. 1a–e. We then calculated three statistical parameters expressing the relationship between the MEXALCA results and the ecoinvent LCIA values: the Pearson's correlation coefficient (PMCC; Eq 4), which indicates the degree of linear dependency, the mean difference between all pairs of results (MD; Eq 5) and the mean absolute difference between all pairs of results (MAD; Eq 6). The mean difference indicates if the method over- or underestimates the impacts on average. The mean absolute difference expresses the average deviation between the calculated impacts and the ecoinvent impacts. These two last parameters are given in percentage of the mean ecoinvent values too (Eq 7 and Eq 8). Table 5 shows these five statistics for the main impacts.

$$PMCC = \frac{\sum_{j=1}^{n}(A_j - \bar{A})(e_j - \bar{e})}{\sqrt{\sum_{j=1}^{n}(A_j - \bar{A})^2}\sqrt{\sum_{j=1}^{n}(e_j - \bar{e})^2}} \tag{4}$$

$$MD = \frac{\sum_{j=1}^{n}(A_j - e_j)}{n} \tag{5}$$

$$MAD = \frac{\sum_{j=1}^{n}|(A_j - e_j)|}{n} \tag{6}$$

$$MD\% = 100\frac{MD}{\bar{e}} \tag{7}$$

$$MAD\% = 100\frac{MAD}{\bar{e}} \tag{8}$$

Table 4 Sensitivity of the different impacts to the main farming inputs per kilogramme of wheat

Modules	Impact sensitivity [%]									
	Non-renewable energy	GWP 100a	Photochemical ozone formation	Nutrient enrichment	Acidification	Aquatic ecotoxicity 100a	Terrestrial ecotoxicity 100a	Human toxicity 100a	Water use	Land use
Variable machinery use	2%	1%	3%	0%	1%	0%	0%	2%	0%	0%
Tillage machinery use	6%	4%	9%	0%	2%	0%	0%	5%	0%	0%
N fertiliser use	19%	39%	12%	61%	53%	0%	0%	14%	0%	0%
P fertiliser use	3%	2%	2%	3%	3%	2%	2%	4%	0%	0%
K fertiliser use	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Pesticide use	2%	1%	2%	0%	0%	68%	67%	13%	0%	0%
Irrigation	55%	16%	35%	0%	4%	0%	1%	45%	186%	0%
Drying	1%	0%	0%	0%	0%	0%	0%	0%	0%	0%

The sensitivity is expressed in percent and corresponds to the mean absolute variation in the impacts value when successively varying a farming input from its median value to its 10% and 90% quantiles

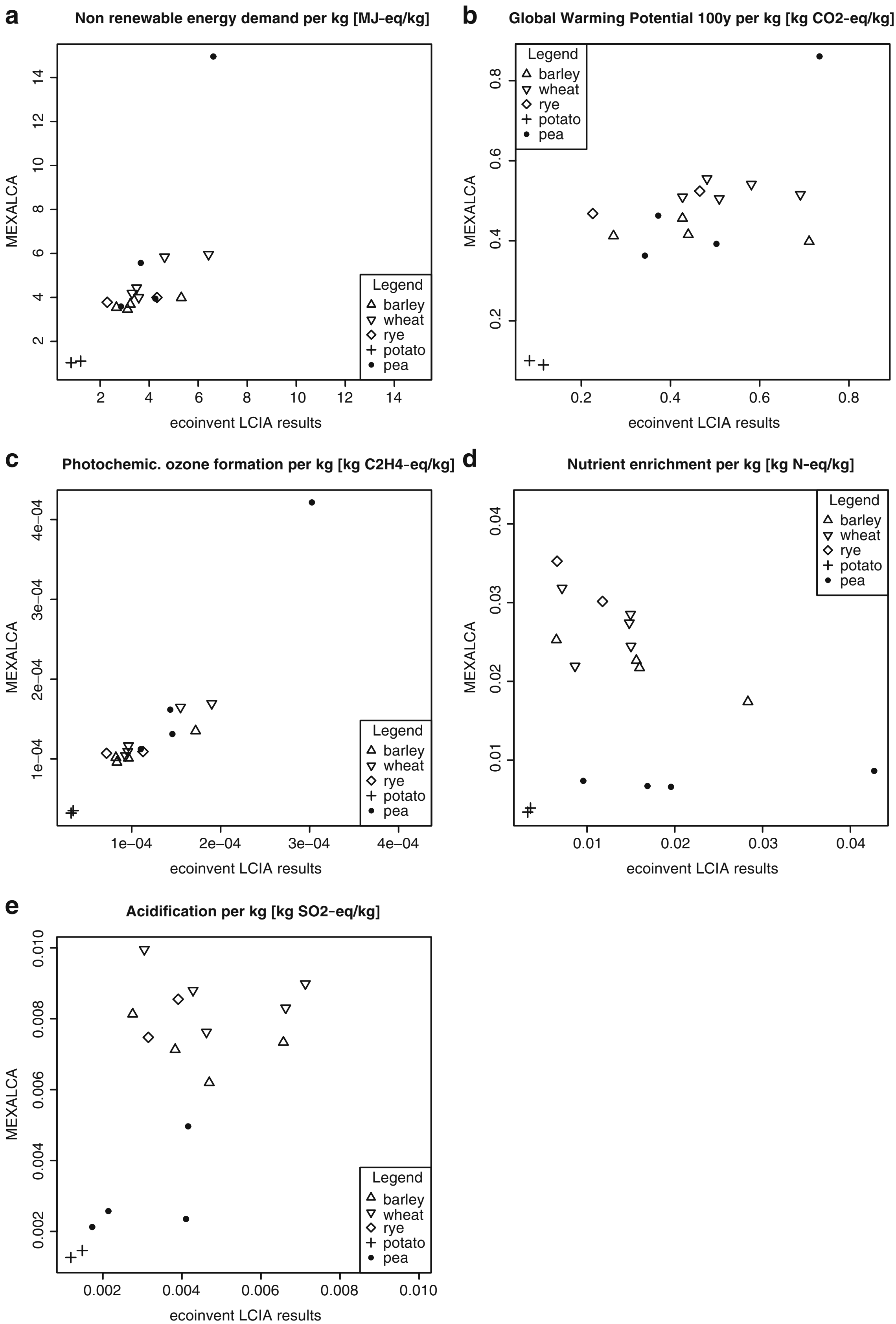
a
Non renewable energy demand per kg [MJ-eq/kg]
MEXALCA
ecoinvent LCIA results
2 4 6 8 10 12 14
Legend
barley
wheat
rye
potato
pea
b
Global Warming Potential 100y per kg [kg CO2-eq/kg]
0.2 0.4 0.6 0.8
c
Photochemic. ozone formation per kg [kg C2H4-eq/kg]
1e−04 2e−04 3e−04 4e−04
d
Nutrient enrichment per kg [kg N-eq/kg]
0.01 0.02 0.03 0.04
e
Acidification per kg [kg SO2-eq/kg]
0.002 0.004 0.006 0.008 0.010

Table 5 Comparison between MEXALCA and ecoinvent

Impacts	Unit	*n*	PMCC	MD	MD%	MAD	MAD%
Non-renewable energy demand	MJ-eq kg^{-1}	17	+7.6E-01	9.0E-01	+24.8%	1.2E 00	+33.0%
Global Warming Potential	kg CO_2-eq kg^{-1}	17	+7.5E-01	1.1E-02	+2.5%	9.2E-0.2	+21.3%
Photochemical ozone formation	kg C_2H_4-eq kg^{-1}	17	+9.4E-01	1.1E-05	+9.6%	2.0E-05	+17.0%
Nutrient enrichment	kgN-eq kg^{-1}	17	−1.9E-01	4.8E-03	+34.2%	1.3E-02	+92.6%
Acidification	kg SO_2-eq kg^{-1}	17	+6.2E-01	2.2E-03	+57.9%	2.4E-03	+63.43%

The Pearson's correlation coefficient, the mean difference, the mean difference expressed in percentage of the mean ecoinvent values, the mean absolute difference and the mean absolute difference expressed in percentage of the mean ecoinvent values are presented, respectively. *n* is the number of points available for the comparison in both ecoinvent and MEXALCA. It encompasses wheat (five points), barley (four points), rye (two points), potato (two points) and protein pea (four points)

A_j is the jth MEXALCA result; $\bar{A}$ is the mean MEXALCA results; e_j is the jth ecoinvent value, $\bar{e}$ is the mean ecoinvent value and n is the number of values in both MEXALCA and ecoinvent.

MEXALCA performs quite well for the energy demand, GWP and ozone formation assessments. MEXALCA results and ecoinvent values are highly correlated (from 0.75 to 0.94). The method overestimates the impacts by 17.2% to 32.7% in average. MEXALCA does not perform well for nutrient enrichment (negative correlation and high MD% and MAD%) and performs relatively poorly for acidification (positive correlation of about 0.6 and important MD% and MAD%). This is probably explained by the lack of consideration of the pedo-climatic conditions which are essential for a good assessment of these two regional environmental effects (Toffoletto et al. 2007) but which are often neglected in LCAs (Potting and Hauschild 2006). Toxicity categories could not be tested against ecoinvent datasets, since numerous characterisation factors for pesticide active ingredients have been added or updated in our study, and the methodological background is different in ecoinvent compared to our calculations. We think, however, that extrapolation should not be applied to toxicity impact categories, since each active ingredient has very different toxicological properties. All active ingredients have to be accurately known in order to perform a solid assessment of toxicity. It was not possible to test the estimation power of MEXALCA for crop production in developing and least developed countries because of the lack of data in current databases like ecoinvent. Special care is therefore needed when interpreting results for such countries.

6 Discussion

MEXALCA enables a rough environmental assessment in a very short time. Impacts can be evaluated for all producing countries without requiring large amounts of data. Furthermore, it provides a realistic estimate for the variability of the impacts on a global scale and a sensitivity analysis based on realistic inputs values can be performed. The validation shows that the method tends to overestimate the impacts on average. An overestimation between about 15% and 30% is expected for energy demand, GWP or ozone formation.

6.1 Modelling assumptions

Several modelling assumptions have been applied for the development of MEXALCA. These imply limitations relating to:

1. Factors which were not considered.
2. Modelling simplifications.
3. Quality of the underlying data.

6.1.1 Factors not considered

Manure and other organic fertilisers have not been taken into account. This can lead to under- or overestimations of certain impacts. An additional module for organic fertilisers could be added, but the key problem would be the development of an estimator for the new input 'organic fertiliser use' (scarce information on the use of organic fertilisers). This is an interesting aspect which should be further explored in the future.

Subsistence farming is not in scope. MEXALCA is not appropriate for the assessment of non-mechanised productions or those which have very low use of external inputs (fertilisers or pesticides).

Organic production has been excluded of the MEXALCA design. However, only 0.7% of the world agricultural area is managed by organic farming (Willer and Klicher 2009), and there are no systematic statistics on organic yields and no reliable data about the use of the

different farming inputs in organic production across the world. Therefore, MEXALCA cannot be used in its current version for the assessment of organic production nor for the comparison between organic and conventional farming.

6.1.2 Modelling simplifications

It is assumed that the minimal field operations required to grow a crop (sowing, seed input, machinery operations for base fertilisation and harvest) are the same all around the world. This assumption is reasonable when assessing conventional production for commercial purposes, since the same types of machines are needed to ensure acceptable yields and a standardised product quality. Differences in size of the machines used for minimal field operations can occur between two countries but are not considered in the method.

The hypothesis is made that the impacts engendered by a unit of farming input are the same everywhere. We do not take into account the characteristics of the environment (soil texture, precipitations, hydrology of the region or microbial activity), which is in accordance with many LCA approaches (as shown by the large use in LCA of the IPCC coefficients (IPCC 2006) to model the nitrogenous emissions).

When extrapolating from the original country to the target countries, only the amounts of farming inputs are varied, their types are kept unchanged. This is particularly problematic for pesticides (active ingredients lead to toxicity potentials which can vary by several orders of magnitude) and for fertilisers (urea which is widely used across the world is not so common in Europe).

6.1.3 Quality of the underlying data

The original inventory plays a critical role in MEXALCA since it is the starting point of the whole extrapolation. Great care should therefore be taken to define the system and calculate the emissions in the original country. A good way to obtain a robust original inventory would be to average several inventories.

Using the estimators instead of accurate data for the farming inputs is already an approximation; the impacts calculated in this way are hence approximations too. The estimators for the inputs are based on FAOSTAT data (FAO 2009), which summarise statistics reported by governmental authorities. These data are not always reliable and sometimes contain errors.

6.2 Assessing variability and uncertainty

Huijbregts (2001) distinguishes between variability and uncertainty in LCA. Variability corresponds to the actual heterogeneity of the systems considered, while uncertainty reflects the lack of knowledge and the inability to quantify exactly the processes under consideration (Basset-Mens et al. 2006). Variability is divided into spatial, temporal and variability between systems, uncertainty into parameter uncertainty, model uncertainty and uncertainty due to choices (Huijbregts 2001). Referring to these definitions, the MEXALCA method aims at reflecting spatial variability and variability between systems to a certain extent (differences in farming systems between countries). Temporal variability could also be considered by using statistics from different periods for the estimation of yields, production volumes and the agricultural indices. Only the variability of the impacts between the countries is considered, not the potentially high variability within a given country (Nemecek and Kägi 2008). For this, it would be necessary to use regional statistics, which would be appropriate especially for very large countries like China or the US.

7 Conclusions and recommendations

7.1 Extrapolation using MEXALCA

This study describes an extrapolation method for agricultural LCIA, which allows for the speedy generation of new LCIA data from available agricultural statistics combined with existing LCI. The method has been applied to several crops. It has shown a good practicability and important time savings compared to traditional detailed LCA approaches. This procedure offers several advantages over a streamlining approach: the conservation of an in-depth understanding of the system, the flexibility of the method or the variability assessment.

As with any extrapolation method, it entails uncertainties related to the methodological simplifications and data sources (highlighted in Section 6).

However, MEXALCA has the advantage of allowing the user to evaluate the statistical distribution of the inputs used and of the resulting impacts estimated for production at the multi-country or world scale. The impacts for food commodities are often better represented by a range of LCIA values (values for several producers in several countries or averages with standard deviation or world median with quantiles) than by LCIA data from a single producer. Regional or global LCIA results are often of greater value for the identification of hotspots across a broad range of ingredients or products due to the complex trade structures. In this sense, the method offers an extension of the practical use of LCA by providing some figures at the multi-country scale and by evaluating their variability.

The estimated variability can be further used to carry out a realistic sensitivity analysis (Section 4), based on national statistics for input use.

7.2 Applicability of MEXALCA

MEXALCA is considered appropriate for the environmental assessment of products at multi-country or global scale. It should thus be primarily used for the estimation of the range of LCIA values of a product across the world (median and variability) or across large areas. In our opinion, another reasonable use of the method is for the assessment of ingredients representing a low percentage of a complex product or for updating existing secondary data. It may also serve the purpose of filling data gaps in the application of carbon footprinting approaches and standards. The variability assessment could be particularly helpful in the context of carbon labelling to avoid the use of single number outputs to describe whole portfolios. Extrapolation cannot replace a detailed assessment using traditional LCA for accurate assessment at the country scale, for detailed comparison of countries and for specific cases such as organic farming. For product retailers and sellers, MEXALCA (associated with an impact assessment of the other significant processes like transport, packaging or storage) may be useful to assess the impact variability of the products sold and to identify “hot spots” in the product portfolio. MEXALCA cannot be used to select suppliers because it does not address the individual differences in farm management. MEXALCA is intended to be a complementary approach to traditional LCA and not a substitute.

7.3 Outlook

MEXALCA has been tested so far for geographical extrapolation (applied to eight crops) and its applicability for product extrapolation will be analysed in the future. Whilst simplified methods such as MEXALCA are useful for the various applications outlined in this paper, it is still likely that growing public interest in the environmental impact of products will increase the demand for transparency of information related to specific production processes. When relevant, more information on the origin and the production conditions of raw materials should be sought and detailed LCA have to be conducted. This investment would be rewarded by an enhanced amount of better quality LCI and LCIA data. Knowledge of the production systems would be improved, further informing strategic decisions for sustainability. However, for commodities bought on the open market this information may, by definition, be impossible to gather. In such cases, methods like MEXALCA that capture the range of impacts caused by the variable production conditions may prove to be the only feasible way forward; results will still be robust enough to inform strategic decision making.

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